FRACTAL DIMENSION AS A FEATURE FOR ADAPTIVE ELECTROENCEPHALOGRAM SEGMENTATION IN EPILEPSY

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Abstract-**In previous studies the fractal dimension (FD) has been shown to be a useful tool to detect non-stationarities and transients in biomedical signals like electroencephalogram (EEG) and electrocardiogram (ECG). The changes in FD are shown to characterise alterations in EEG due to changes in physiological states of brain, not only in normal but also in pathological functioning like epilepsy. The importance of long-term EEG monitoring for clinical evaluation in epilepsy has been also emphasised. Adaptive EEG segmentation and classification of the obtained segments have been addressed to be a convenient solution to the problem of visual inspection of huge EEG data sets. The performance of adaptive segmentation plays an essential role in correct evaluation of the recordings. Thus, our aim in this study is to analyse the FD as a feature for adaptive EEG segmentation and compare its performance with those of previously used features on epileptic EEG data.**

Keywords **– EEG, adaptive segmentation, fractal dimension, epilepsy**

I. INTRODUCTION

The importance of long-term EEG monitoring for differential diagnosis and therapy evaluation in epilepsy is described in several studies. Logar [1] mentions long-term EEG monitoring as a tool improving the diagnostic value of standard EEG recordings and providing additional necessary diagnostic information. Lopes da Silva [2] stresses the essentiality of pattern recognition and quantification of EEG for determination of different physiological states in anaesthesia, sleep and other long duration recordings.

The long-term EEG recordings yield, however, the problem of analysing and quantifying huge data sets. Adaptive segmentation and clustering of the obtained segments of EEG have been addressed to be a convenient solution to the problem of visual inspection of the huge EEG data sets [3-5]. The performance of adaptive segmentation, which depends highly on the feature(s) used, is a key issue in correct evaluation of the data with this approach.

FD is commonly applied in both system and signal analysis. In non-linear system analysis it is used for representing attractors which have fractional dimensions. The most commonly used algorithm for this purpose is the Grassberger and Proccacia method [6]. In signal processing, FD is addressed for detecting non-stationarities in time series. It has been shown to be a useful tool to detect transients also in EEG [7, 8]. Thus, in this study we examine the FD as a feature for adaptive EEG segmentation in epilepsy.

II. METHODOLOGY

A. Adaptive Segmentation Algorithm

The adaptive segmentation algorithm used has been proposed by Silin and Skrylev [9]. The algorithm uses two successive windows moving on the time series in which the selected feature(s) is/are calculated. A measure difference function is obtained through the difference of feature(s) in the two successive windows. The adaptive segment boundaries are then assigned to be the local maxima of this measure difference function.

In the original form of the algorithm spectral change measure calculated by fast Fourier transform (FFT) is used as the feature to detect non-stationarities. Because the computation of the spectral change measure by FFT is inefficient, the method has been modified by Värri [10], who introduced a difference measure composed of a frequency measure, F_{dif}, estimated by the sum of the difference of consecutive signal samples, and an amplitude measure, A_{dif}, the sum of the absolute values of the signal in the relevant windows [3, 10].

$$F_{dif} = \sum_{i=1}^{wl} | x_i - x_{i-1} | \tag{1}$$

$$A_{dif} = \sum_{i=1}^{wl} | x_i | \tag{2}$$

where $wl =$ window length, x_i is the i^{th} data point. The measure difference function, G, is then defined as,

$$G_j = k_a \mid A_{dif\ j+1} - A_{dif\ j} \mid + k_f \mid F_{dif\ j+1} - F_{dif\ j} \mid \tag{3}$$

where k_a and k_f are coefficients for amplitude and frequency measures respectively, j is the j^{th} window analysed.

In order to avoid excessive segmentation due to redundant small segments, Krajca [3] introduced a threshold for the measure difference to the algorithm. The local maxima of the function G, which are over the assigned threshold are accepted to be positioning the segment boundaries. Krajca [3] suggested also values for k_a and k_f ($k = 1_a$, $k_f = 7$) which were determined according to results of experiments with simulated signals.

B. Fractal Dimension

In signal processing, there are several methods to approximate the FD in time variant signals. In the study by Esteller [11] the most prominent methods for FD computing used in EEG analysis are compared. It is concluded that the Katz's algorithm is the most consistent

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Abstract

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method for discrimination of epileptic states from intercranial EEG. Therefore, we selected Katz's algorithm for fractal dimension calculation in our application. According to Katz, D, the FD of a curve is defined as:

$$D = \frac{\log_{10}(L)}{\log_{10}(d)} \tag{4}$$

where L is the total length of the curve, and d is the diameter estimated as the distance between the first data point and the data point that gives the largest distance. Normalising the distances with y, the average distance between successive data points, we get:

$$D = \frac{\log_{10}(L/y)}{\log_{10}(d/y)} \tag{5}$$

Defining $n = L/y$, the number of steps in the curve,

$$D = \frac{\log_{10}(n)}{\log_{10}(d/L) + \log_{10}(n)} \tag{6}$$

For FD calculation Katz's algorithm is implemented and tested on simulated data which is produced using the deterministic Weierstrass cosine function [12]:

$$W(t_i) = \sum_{n=0}^{\infty} \omega^{-nH} \cos(\omega^n t_i) \tag{7}$$

where ω>1 and 0 < H < 1, and the fractal dimension of the generated signal is given by D = 2 - H.

For the adaptive segmentation application, we assigned the FD as the only measure for the function G. Thus the corresponding G function is,

$$G_j = |D_{j+1} - D_j|, \qquad j = 1, ..., N-1 \tag{8}$$

where N is the total number of windows in analysis.

The measure difference function G is normalised by $G_j / \max(G)$ within the interval of analysis in order to be able to have standard values for the thresholds.

C. EEG Data

In order to compare the performances of the features, 30 different epileptic patterns are chosen randomly from clinical EEG data. The signals are acquired according to international 10/20 system with a sampling rate of 128 Hz.

III. Results and Discussion

The first observation was that the FD decreased in epileptic pattern intervals (fig. 1, 3, 5, 7). Secondly, we observed that in 14 epileptic patterns out of 30, the FD was more sensitive to the end points of the patterns whereas the features proposed by Värri detected some redundant boundaries within the pattern before the end points were detected, that is, in order to detect the end points of the pattern, the threshold has to be decreased meaning that the redundant segment boundaries are needed to be included (eg. Pattern1 (fig. 1 and 2), Pattern 2 (fig. 3 and 4), Pattern 4 (fig. 7 and 8)). Additionally, there observed to be 3 patterns for which the Värri measures failed to detect the end points correctly such as the example pattern 3 (fig. 5 and 6). The results for the rest 13 patterns were similar.

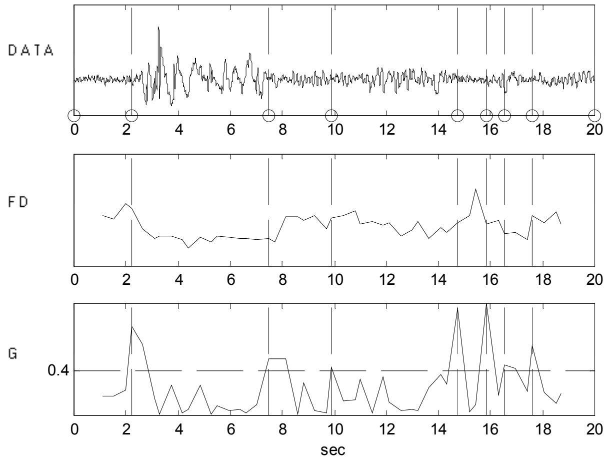


Fig. 1. Segmentation result of FD, pattern 1.
Window width=1.1 sec, overlapping=60%, threshold=0.4.

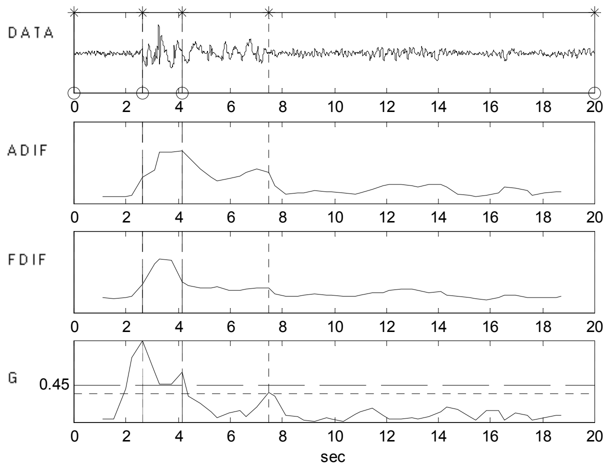


Fig. 2. Segmentation result of Värri measures, pattern 1.
Window width=1.1 sec, overlapping=60%, threshold=0.4 (*) and 0.45 (o).

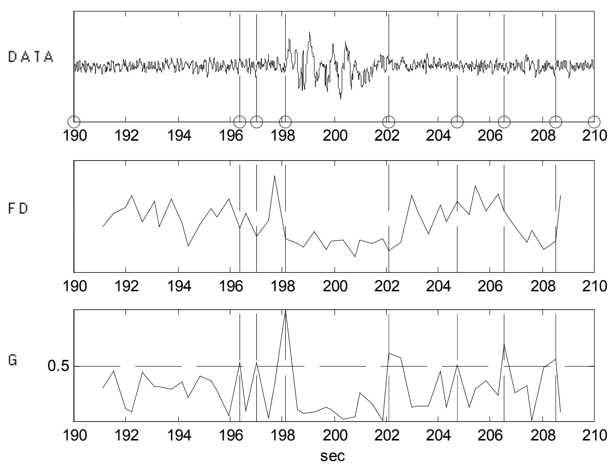


Fig. 3. Segmentation result of FD, pattern 2.
Window width=1.1 sec, overlapping=60%, threshold=0.5.

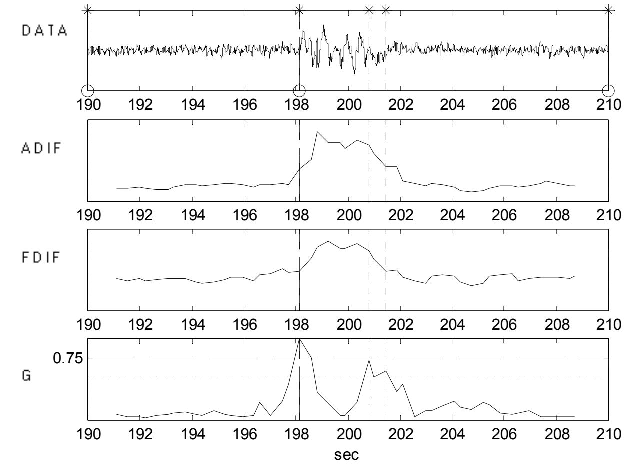


Fig. 4. Segmentation result of Värri measures, pattern 2.
Window width=1.1 sec, overlapping=60%, threshold=0.6 (*) and 0.75 (o).

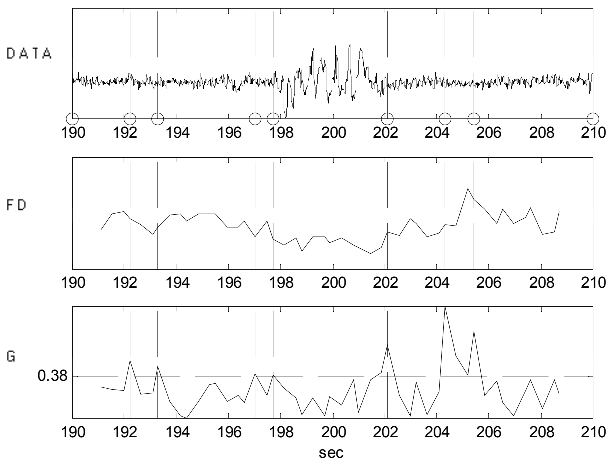


Fig. 7. Segmentation result of FD, pattern 4.
Window width=1.1 sec, overlapping=60%, threshold=0.38.

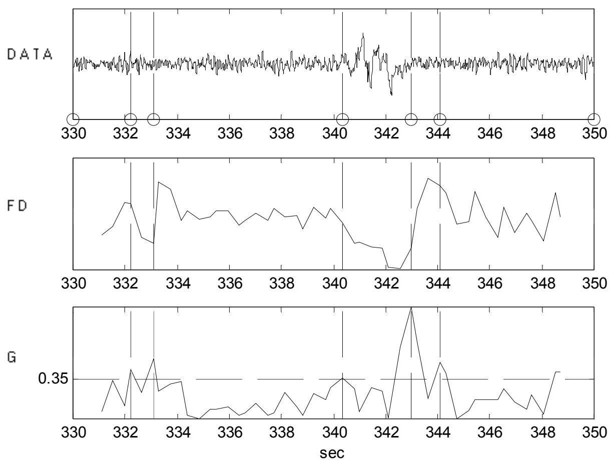
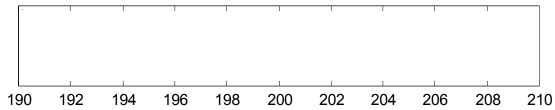


Fig. 5. Segmentation result of FD, pattern 3.
Window width=1.1 sec, overlapping=60%, threshold=0.35.



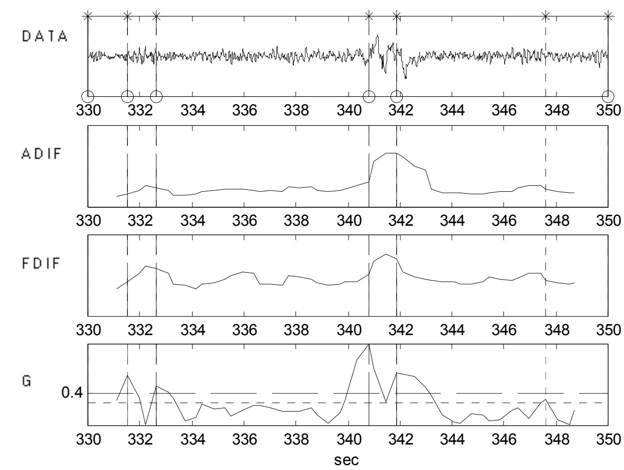


Fig. 6. Segmentation result of Värri measures, pattern 3.
Window width=1.1 sec, overlapping=60%, threshold=0.3 (*) and 0.4 (o).

The adaptive segmentation al thm has t hree important p

The window width should not be selected very large in order to be able to detect non-stationarities finer. It should also conform to the number of data points required to calculate the selected feature sufficiently. Additionally, the smaller the window width is, the higher the computational load is.

(smaller step length), th o he number of segm s found are. This means a longer computation time and increase in the number of redundant segments. However, if the overlapping is too small the necessary segment boundaries to be detected can be missed.

The threshold plays an important role in sensitivity of the algorithm. The higher the threshold is, the less sensitive the algorithm to the non-stationarities is. If the threshold is too low then there is again the problem of redundant segmentation.

In our software realization these parameters can be input as desired so that their influences on the performance of the algorithm can be observed. The software also allows the automation of the analysis where we assign the window width and the overlapping a priori according to experimental results of the algorithm. For automated analysis, the threshold for FD is determined adaptively according to the distribution of the values of FD through the data interval analyzed. The median value in the distribution is assigned to be the threshold.

V. Conclusion

The use of FD as a feature in adaptive segmentation of epileptic EEG has advantages over the previously used parameters. First one is that FD can be used as a single feature without the need of any coefficients to combine different measures. Secondly, its higher sensitivity to end points of the epileptic patterns yields a better reduction of redundant segmentation, which can be also interpreted as FD being more stable within the epileptic pattern interval. These results need to be verified on a larger set of different epileptic patterns.

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